

ADDIS ABABA UNIVERSITY
ADDIS ABABA INSTITUTE OF TECHNOLOGY
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING



**SPATIOTEMPORAL MONITORING OF URBAN SPRAWL IN SHEGER
CITY IN OROMIA USING GIS AND REMOTE SENSING**

A thesis submitted to the School of Graduate Studies of Addis Ababa University Presented in
Partial Fulfillment of the Requirement for the Degree of Master of Science
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A Thesis

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UNDERTAKING

I certify that the research work titled "Spatiotemporal Monitoring of Urban Sprawl in Sheger City in Oromia using GIS and Remote Sensing" is my work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged/referred.

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ABSTRACT

Urban sprawl, characterized by the rapid expansion of urban areas into rural lands, poses significant challenges to sustainable development. This research investigates urban sprawl in Sheger City, Ethiopia, utilizing Geographic Information Systems (GIS) and remote sensing techniques to analyze spatial growth patterns over 30 years from 1991 to 2022. Classification of land use types was performed using the Maximum Likelihood Algorithm, and accuracy assessment was conducted using Google Earth-measured sample points and an error matrix. In addition to the classification Urban sprawl indices is carefully selected and used to in quantifying and characterizing urban change. From this study five indices were used Urban Expansion Intensity Index (UEII), Normalized Difference Built-up Index (NDBI), Urban Index (UI), New Built-up Index (NBI), and Band Ratio for Built-up Area (BRBA) to quantifying and characterizing urban sprawl. Accuracy analysis revealed an accuracy range of 81.43% to 99.71% and Kappa statistics from 0.7936 to 0.9968, indicating effective land cover classification. Built-up areas expanded from 59.87 km² in 1991 to 200.07 km² in 2022. The UEII showed moderate to high expansion during 1991-2001 (0.1987), 2001-2011 (0.0522), and 2011-2022 (0.5631). NDBI, UI, and NBI indicated significant urban growth, especially from 1991 to 2001, with more balanced development by 2022. BRBA highlighted major expansions from 1991 to 2001, with stable growth afterward. The study concludes that Sheger City has experienced significant urban expansion over the past three decades, with varying intensities across different periods. The findings underscore the importance of monitoring urban growth to manage and mitigate the negative impacts of urban sprawl. Effective urban planning and management strategies are essential to ensure sustainable development and address the challenges associated with rapid urbanization. This research provides valuable insights for urban planners and policymakers, contributing to the sustainable development of Sheger City and potentially serving as a model for other rapidly urbanizing.

Keywords: *Urban Sprawl, UEII, NDBI, UI, NBI, BRBA*

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LIST OF ACRONYM

GPS	Global Positioning System
UEII	Urban Expansion Intensity Index
NDBI	Normalized difference built-up index
UI	Urban Index
NBI	New built-up index
BRBA	Band ratio for the built-up area

1. INTRODUCTION

1.1 Background

Urban sprawl, synonymous with urbanization, describes the expansion of urban areas into surrounding rural land, often resulting in low-density residential development. This phenomenon leads to the outward spread of cities and their suburbs, consuming more rural areas. It is characterized by the conversion of undeveloped land into residential and commercial areas, driven primarily by population migration seeking improved living conditions. Urban sprawl has been a persistent global trend since the industrial era, with economic growth and urbanization driving the encroachment of cities into agricultural lands (Azadi et al., 2011a; Paul and McKenzie, 2013).

Despite efforts to control urban sprawl, it has continued to escalate dramatically. Between 1990 and 2014, urban sprawl increased by 95% worldwide, with built-up areas expanding at an average rate of approximately 1.2 Km² (Behnisch et al,2022). The term "urban sprawl" is often used in a negative context, highlighting the environmental impacts of rapid industrialization and urban growth. It has become a focal point for critics advocating for more controlled urban development.

Ethiopia, despite being one of the least urbanized countries in Africa, is experiencing rapid urbanization. Ethiopia has undergone tremendous urbanization, which has significantly altered the landscape of the city (Ermias et al., 2020). A shift in the previous pattern of land use or land cover has resulted in urban expansion or outskirt growth. The transformation of undeveloped land into built-up space is not uniform in all directions.

The Oromia Special Zone encompassing Finfinnee (Addis Ababa) has witnessed a rapid expansion of built-up areas and sporadic spatial growth throughout Ethiopia, as highlighted by Terfa et al. (2020). Urban sprawl, the uncontrolled expansion of urban areas into surrounding rural landscapes, is a significant challenge faced by cities worldwide. In Sheger City, located in the Oromia region, the rapid growth and expansion of urban areas have led to various environmental, social, and economic impacts.

To address this issue, spatiotemporal monitoring using Geographic Information Systems (GIS) and remote sensing techniques has become increasingly important. Spatiotemporal monitoring of urban sprawl in Sheger City is facilitated through the utilization of GIS and remote sensing technologies. Through analyzing satellite imagery and GIS data from different periods of 30 years, and using urban sprawl indices used to measure and quantify the extent and characteristics of urban sprawl in the area. The study aims to track the expansion of urban areas and identify patterns of sprawl.

The findings of this study will provide valuable insights for urban planners and policymakers in Sheger City to effectively manage urban growth and mitigate the negative impacts of urban sprawl. Through the use of GIS and remote sensing, this research contributes to the sustainable development of Sheger City and serves as a model for other cities facing similar challenges.

1.2 Statement of the Problem

Urbanization is a prominent theme in contemporary development discourse, shaping human settlements worldwide. The increasing interest in modeling and analyzing urbanization underscores the importance of understanding the growth rate, pattern, and extent of urban expansion to provide essential amenities for growing populations. In Ethiopia, the concentration of private investments around major urban centers like Addis Ababa has intensified concerns about displacement, particularly due to the outward expansion of these centers encroaching on fertile agricultural lands crucial for local livelihoods. Urban sprawl, characterized by scattered settlements with low building densities, requires significant infrastructure development, leading to adverse environmental and climatic impacts. According to Berehanu et al (2023) industrialization, highway road construction, hotel, residential development, and other formal and informal businesses undertaking in great pace the expansion urban area surrounding the capital city of Addis Ababa.

Urban planners require such information to effectively model urban sprawl, a phenomenon exacerbated by various factors such as commercial farming, park protection, resettlement, road construction, and overall urban expansion, leading to population displacement. There are the limited number of studies conducted on quantifying the extent and detecting the pattern of urban sprawl in Ethiopia using GIS and Remote Sensing. There are a quite significant number of studies conducted on the impact of urban sprawl in altering land uses especially the impact it has

on the consumption of agricultural land on the outer skirts of cities. A notable contribution on quantifying the rate of urban sprawl and mapping was made by (Sewunet S.,2017) for the city of Addis Ababa and its surroundings.

Recently a similar study was conducted in Ethiopia by (Dribia et al.,2016) on the major drivers of urban sprawl and its impacts on land use conversion in the peri-urban kebeles of Dukem town, one of the towns in the Oromia Special Zone surrounding Addis Ababa city, also Urban Horizontal Expansion and Its Effect on Rural Community Livelihood in the Oromia Special Zone Surrounding Finfinne (OSZSF) Towns and Addis Ababa City by (Giorgis et al 2023) whereas all the research were conducted focusing on specific towns Dukem, Sebeta or some part of the Shgere City but the recent establishment of Sheger City by the Oromia regional state, merging towns surrounding Addis Ababa like Sebeta, Burayu, Legatafo, Lededadi, Sululta, and Gelan, reflects efforts to address the sluggish development of cities and displacement of farming communities. The city administration's crackdown on illegal construction underscores the need for effective urban planning and management.

This study aims to assess the expansion rate and pattern of urban sprawl in Sheger City to inform future decision-making processes. Understanding the dynamics of urban sprawl in Sheger City is crucial for sustainable development and the preservation of agricultural lands and natural areas.

1.3 Objective

1.2.1 General objective

The main objective of the study will be to examine the urban Sprawl of the study area over the past 30 years by assessing the magnitude of the urban expansion using remote sensing and GIS.

1.2.2 Specific objective

The main objective of the study is

- To evaluate land use/land cover change in Shger City during 1991-2022.
- To identify the patterns of urban sprawl in Sheger City from 1991 to 2022
- To compute urban sprawl indices to identify the pattern 1992, 2001, 2011, and 2022

1.3 Research Question

- What are the land use land cover changes in Shgere City from 1991 to 2022?
- What patterns of urban sprawl can be identified in Sheger City during 30 years ?
- How do urban sprawl indices vary over time, especially in 1992,2001, 2011 and 2022?

1.4 Significance of this Study

The study provides the potential for valuable insights into the dynamics of urban sprawl in Sheger City and its surrounding areas. Understanding the expansion rate, pattern, and extent of urban sprawl is essential for several reasons: The findings will inform urban planners and policymakers about the current and potential future trends of urban sprawl. This information is crucial for developing effective strategies and policies to manage urban growth, ensure sustainable development, and mitigate negative environmental and social impacts.

Urban sprawl often leads to the loss of agricultural land, fragmentation of natural habitats, and increased pressure on natural resources. By identifying the areas most affected by urban sprawl, this study can help prioritize conservation efforts and promote sustainable land use practices. According to social implications, Urban sprawl can have significant social implications, such as displacement of communities, changes in land ownership patterns, and increased demand for social services. Understanding these implications can help develop strategies to mitigate negative effects and promote inclusive development. Additionally, Urban sprawl necessitates the expansion of infrastructure, such as roads, utilities, and services, to accommodate the growing population. By mapping the extent of urban sprawl, this study can assist in planning and prioritizing infrastructure development projects. Based on the findings Policy policymakers use the findings of this study as a basis for developing policies and regulations to manage urban sprawl effectively. This includes zoning regulations, land use planning, and incentives for compact urban development.

Overall, this study is significant as it provides a comprehensive understanding of the dynamics of urban sprawl in Sheger City, which can inform sustainable urban development practices and policies in the region.

1.6 Scope

This research attempts to study the urban expansion specifically, Spatiotemporal Monitoring of Urban Sprawl in Sheger City in Oromia using GIS and Remote Sensing.

1.7 Limitation

The study will utilize Geographic Information Systems (GIS) and Remote Sensing tools to quantify the rate and detect patterns of urban sprawl within the city's boundaries. It excludes other urban centers outside Sheger City and will not delve deeply into the socio-economic implications of urban sprawl, such as livelihoods or displacement impacts, though these are recognized as related concerns. Furthermore, the study does not aim to analyze all drivers of urbanization comprehensively but will instead focus on spatial and pattern analysis of urban expansion in the study area. The findings will serve urban planners, policymakers, and local authorities in Sheger City, providing insights for better management of urban sprawl and the preservation of agricultural lands.

1.8 Structure of the Study

The overall thesis is organized under five chapters as follows, Introduction, Literature review, Methodology, Result and Discussion, and Conclusion and Recommendations.

Chapter 1: explains the necessity of the background of the study and states the problems, Research question, objectives of the study, scope of the study, and limitations of study.

Chapter 2: a literature review was carried out to have a clear understanding of the study. The chapter briefly reviews the list of the literature that is reviewed to develop the concepts.

Chapter 3: describes the study area, and all methodology of the study that denoted step by step procedure following which the study was conducted. In this section, the data collection, processing, and analysis techniques will be elaborated and the procedures of data analysis will be briefly discussed.

Chapter 4: Results and Discussions

Chapter 5: Conclusion and Recommendation includes the recommendations that are stated considering the findings of the study and finally the conclusion which is drawn through the whole research.

2. LITERATURE REVIEW

2.1 Urban sprawl

Sprawl is generally regarded as an unsustainable form of urban development (Torrens and Alberti, 2000) describe the characteristics of sprawl as 'relatively wasteful methods of urbanization, characterized by uniform low density; it is often uncoordinated and extends along the fringes of metropolitan areas with incredible speed. In 2001 Zhang also stated that "urban sprawl results from poorly planned, large scale new residential, commercial and industrial developments in areas previously not used for urban purposes." Commonly, sprawl invades prime agricultural land and resources in the process. Land is often developed in a fragmented and piecemeal fashion, with much of the intervening space left vacant or in use with little functionality.

Urban sprawl refers to the uncontrolled expansion of development around the outskirts of cities, a phenomenon prevalent in both industrialized and developing nations. This pattern disrupts the systematic development of land, hindering economically efficient land use and management, particularly in areas experiencing rapid urbanization. The primary area affected by urban sprawl is the peri-urban zone, where the consequences are most pronounced. In peri-urban communities, development is characterized by scattered, patchy expansion, often leading to fragmented landscapes and discontinuous growth.

Urban sprawl is a global phenomenon; its manifestations vary considerably across regions and countries. In developed economies, such as the United States and parts of Europe, sprawl patterns are well-documented and often associated with suburbanization and automobile dependence. In contrast, rapid urbanization and unplanned growth in many developing countries have led to sprawling megacities characterized by informal settlements, inadequate infrastructure, and environmental degradation. Emerging economies in Asia, Africa, and Latin America face unique challenges related to managing urban expansion while addressing poverty, inequality, and environmental sustainability.

The United Nations projects that 68% of the world's population will live in urban areas by 2050 (UN, 2018). About 90% of this projected urban population growth will come from Asia and Africa, where the size and number of cities will double. Historically, Africa has been predominantly rural, with the exception of some spatially limited imperial cities. In less than two decades, the urban population in Africa has nearly doubled, rising from 290 million in 2000, which represented around 35% of the total population, to 570 million in 2020, or 45% of the total population (UN, 2022). This rapid increase in the urban population has catalyzed many critical urban issues and challenges (Florida et al., 2017) associated with uncontrolled urban expansion.

2.2 Types of Urban Sprawl

Urban sprawl refers to the outgrowth of urban areas caused by uncontrolled, uncoordinated, and unplanned growth. Today, some 56% of the world's population – 4.4 billion inhabitants – lives in cities. This trend is expected to continue, with the urban population more than doubling its current size by 2050, at which point nearly 7 of 10 people will live in cities. With more than 80% of global GDP generated in cities, urbanization can contribute to sustainable growth through increased productivity and innovation if managed well.

However, the speed and scale of urbanization bring challenges, such as meeting accelerated demand for affordable housing, and viable infrastructure including transport systems, basic services, and jobs, particularly for the nearly 1 billion urban poor who live in informal settlements near opportunities. Rising conflicts contribute to pressure on cities as more than 50% of forcibly displaced people live in urban areas. Once a city is built, its physical form and land use patterns can be locked in for generations, leading to unsustainable sprawl. The expansion of urban land consumption outpaces population growth by as much as 50%, which is expected to add 1.2 million km² of new urban built-up area to the world by 2030 Rodrigue, J-P et al. (2020). Such sprawl puts pressure on land and natural resources, resulting in undesirable outcomes; cities represent two-thirds of global energy consumption and account for more than 70% of greenhouse gas emissions.

Low-density Sprawl

Low-density continuous sprawl is a phenomenon caused by the outward spreading of low-density suburban land use that is currently being experienced by many cities in America as their population becomes bigger and bigger and there is no lack of land supply. This highly consumptive use of land for urban purposes is supported by piecemeal extensions of basic urban infrastructure such as water, sewer, power, and roads.

Ribbon Sprawl

Ribbon sprawl is a type of sprawl characterized by a concentration of development along major transportation arteries, primarily roads. While development occurs on land adjacent to the major roads, areas without accessibility to the roads tend to remain as green areas, waiting for conversion into urban land uses when land values increase and infrastructure is extended from the major roads.

Leapfrog Development Sprawl

Leapfrog development sprawl is a scattered form of urbanization with disjointed patches of urban land uses, interspersed with green areas. Leapfrog development may be caused by obvious physical limitations such as prohibitive topography, water bodies, and wetlands or by more subtle reasons such as differences in development policies between political jurisdictions.

2.3 Remote Sensing and GIS for Urban Sprawl

The unprecedented population growth, together with uncontrolled urbanization, forced the cities to expand further to accommodate the urban growth. The urban expansion towards the periphery is regarded as urban sprawl. A rise in the built-up features especially in the urban fringes can be considered as a common characteristic feature of urban sprawl. It is irrefutable that earth observation is a modern science, which studies the earth's changing environment, through remote sensing data such as satellite imagery and aerial photographs. A report published by NASA highlighted the fact that the advances in satellite-based land surface mapping are contributing to the creation of considerably more detailed urban maps, offering planners a much

deeper understanding of the dynamics of urban growth and urban sprawl, as well as associated matters relating to territorial management (NASA 2001). Compared to other applications, remote sensing of urban areas, especially with space-borne sensors, is rather a new topic for the remote sensing community and geographers (Maktav et al. 2005).

Aerial photography has very long archived data records, while satellite remote sensing for earth observation started in 1972 with the first launch of the Landsat satellite. Since 1972, numerous technical improvements have led to the second generation of earth observation satellites, such as advanced Landsat satellites (TM and ETM+), SPOT, and Indian Remote Sensing (IRS) LISS sensors. From 1999 one can distinguish a third generation of earth observation satellites with very high geometric resolution (IKONOS-2, QuickBird-2, OrbView-2, Geoeye-1, Cartosat, etc.). This has led to more and more urban applications using remote sensing data since the requirements regarding the desired level of detail can be fulfilled either by aerial or satellite-based sensor systems. Nowadays, not only these two platforms are complementary, rather satellite sensors are increasingly dominating many application domains including urban analysis.

As a result of development in software, hardware, and remote sensor technologies, there is an increasing demand among cities in developed countries for using remote sensing and GIS to establish an urban information system.

2.3.1 Land use classification

Urban sprawl and land use classification are closely intertwined, impacting the sustainability and functionality of urban areas. Understanding land use patterns is crucial for managing urban growth and mitigating the negative effects of sprawl. This literature review examines key studies on land use classification and its relationship with urban sprawl, highlighting methodologies, findings, and implications for urban planning. Land use classification is the process of categorizing the various uses of land based on criteria such as function, ownership, and physical characteristics. It is fundamental for urban planning, environmental management, and policy formulation.

Remote sensing and Geographic Information Systems (GIS) are widely used tools for land use classification. These technologies provide high-resolution data that can be analyzed to detect land use changes over time. For instance, Lille sand, Kiefer, and Chipman (2015) discuss how satellite imagery and aerial photographs have been instrumental in mapping urban areas and monitoring sprawl.

Recent advancements have seen the application of machine learning algorithms in land use classification. Techniques such as decision trees, random forests, and neural networks enhance the accuracy of land use maps. A study by Xie, Sha, and Yu (2019) demonstrated the effectiveness of convolutional neural networks (CNNs) in classifying urban land uses from high-resolution images. Traditional methods like field surveys and participatory mapping involve ground truthing and engaging local communities in mapping exercises. These methods provide detailed and context-specific data, complementing remote sensing and GIS approaches.

Effective land use classification is crucial for understanding and managing urban sprawl. Accurate and up-to-date land use data enables planners to identify trends, forecast future growth, and implement measures to control sprawl. Land use classification helps in monitoring urban growth patterns and identifying areas experiencing rapid expansion. Studies like those by Seto, Güneralp, and Hutyrá (2012) use land use data to assess the extent and impact of urban sprawl globally. Accurate land use data informs policy decisions related to zoning, land development, and environmental conservation. Implementing land use regulations based on comprehensive data can mitigate the adverse effects of sprawl (Bhatta, 2010). Integrating land use classification with urban planning promotes sustainable development.

Land use classification plays a vital role in understanding and managing urban sprawl. Advances in technology, such as remote sensing, GIS, and machine learning, have significantly enhanced the ability to classify land use accurately and monitor urban expansion. Addressing the causes and consequences of sprawl requires integrated approaches that combine detailed land use data with comprehensive urban planning and policy measures. By leveraging these tools and insights, cities can promote sustainable development and mitigate the adverse impacts of uncontrolled urban growth.

2.3.2 Spectral Indices

Spectral indices, derived from remote sensing data, are vital tools for analyzing urban sprawl. They enhance the ability to monitor, map, and quantify changes in land cover, particularly the expansion of urban areas into rural and natural landscapes. Spectral indices are mathematical combinations of different spectral bands from satellite imagery designed to highlight specific features or conditions on the Earth's surface. They are particularly useful in distinguishing between various types of land cover, such as vegetation, water, and built-up areas.

NDBI is specifically designed to delineate built-up areas. It is particularly effective in monitoring urban growth and sprawl by identifying and quantifying built-up surfaces (Zha, Gao, & Ni, 2003). Also widely used Urban Index is used to enhance the detection of urban features in remote sensing imagery. It is useful in distinguishing urban areas from other land cover types (Kawamura, Jayamanna, & Tsujiko, 1996).

Spectral indices are calculated using the specific formulas. This step involves the application of mathematical operations on the pixel values of the relevant spectral bands (Xu, 2007). The calculated indices are analyzed to assess land cover changes. This analysis often includes time-series analysis to monitor changes over different periods, spatial analysis to map the extent of urban sprawl, and statistical analysis to quantify the impacts (Chen et al., 2010).

The use of spectral indices in studying urban sprawl has significant implications for urban planning and management: Spectral indices provide objective and quantifiable data on land cover changes, enabling informed decision-making in urban planning (Herold, Couclelis, & Clarke, 2005). By identifying areas of rapid urban expansion and their environmental impacts, planners can develop strategies to promote sustainable development and mitigate adverse effects (Seto et al., 2012). Spectral indices can inform policy by highlighting trends in land use changes and identifying priority areas for conservation and development (Alberti, 2005).

Spectral indices are powerful tools for studying urban sprawl, offering detailed insights into land cover changes and urban growth patterns. Advances in remote sensing technology and the development of new indices continue to enhance the capability of researchers and planners to monitor and manage urban sprawl effectively. Integrating spectral indices with urban planning practices can lead to more sustainable and resilient urban environments.

3. METHODOLOGY

3.1 Background of the Study

Sebeta, Burayu, Legatafo, Lededadi, Sululta, and Gelan towns, which surround Addis Ababa from all directions, are now clustered as a single city under a single mayoral administration. And the administration is operational already. cited as deputy mayor of the new Sheger city has confirmed that the six towns are now under Sheger city administration. It has 12 sub-cities, 36 districts, and 40 rural kebeles (these are now county administrations in Ethiopia).

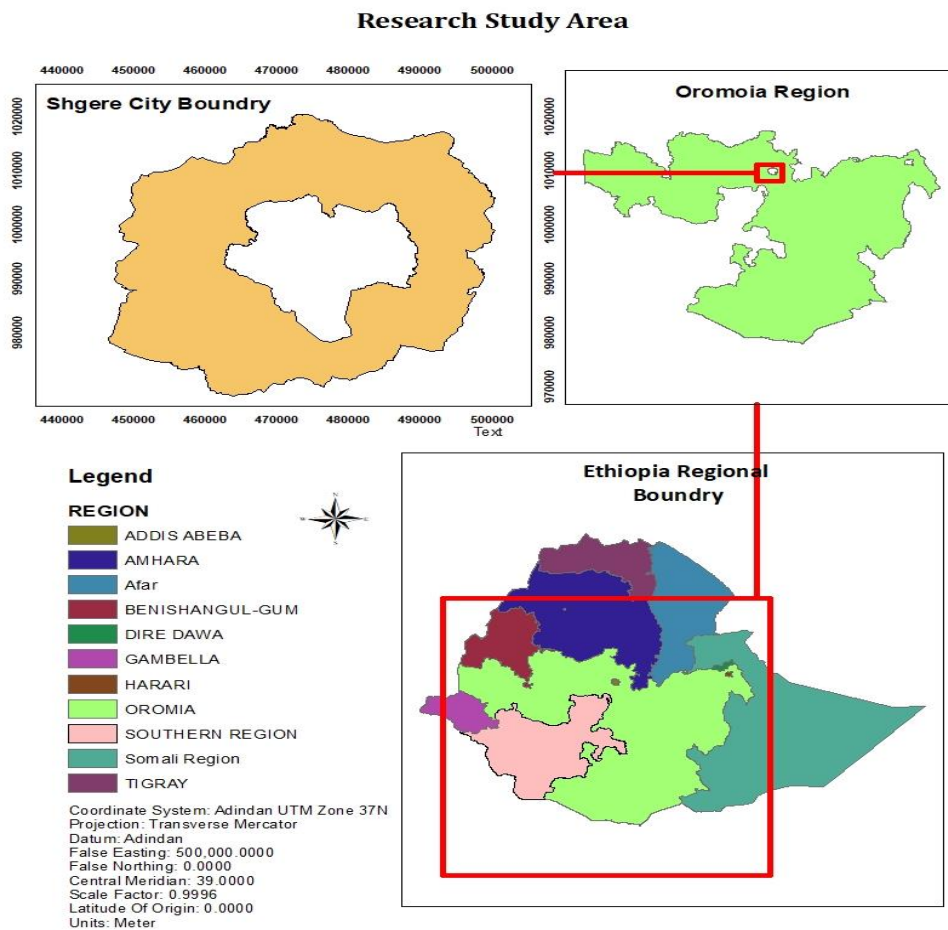


Figure 1: Geographical Location of the study area

3.3.1 Data Collection Methods

The administrative boundary data were collected from Sheger City administrative office and demographic data from the Census of Ethiopia projection (2011) were used. The spatial analysis Satellite image for land use classification was collected from the United States Geological Survey (USGS) (<https://earthexplorer.usgs.gov/>) for the years 1991, 2001, 2011, and 2022.

Table 1: Satellite image information and sources

Type of data	Satellite used	Resolution /scale	Path/Raw	Year/Month/Date Acquired
Landsat TM image	Landsat 4-5 Thematic Mapper C1 Level-1	30 m	168/54	1991-02-04
Landsat TM image	Landsat 4-5 Thematic Mapper C1 Level-1	30 m	168/54	2001-03-03
Landsat TM image	Landsat 4-5 Thematic Mapper C2 Level-2	30 m	168/54	2011-01-10
Landsat OLI image	Landsat 8 OLI/TRIS C1 Level -1	30 m	168/54	2022-03-05
Administrative boundary map	Shapefile format	Shegere City Administrative Office		

These data sets were used for the land cover and land use classification analysis. Table 1 shows the path and row details of satellite images. For the study purpose, the cloud-free satellite images were chosen in the consecutive month of each year to reduce the discrepancy of images due to periodical or seasonal changes.

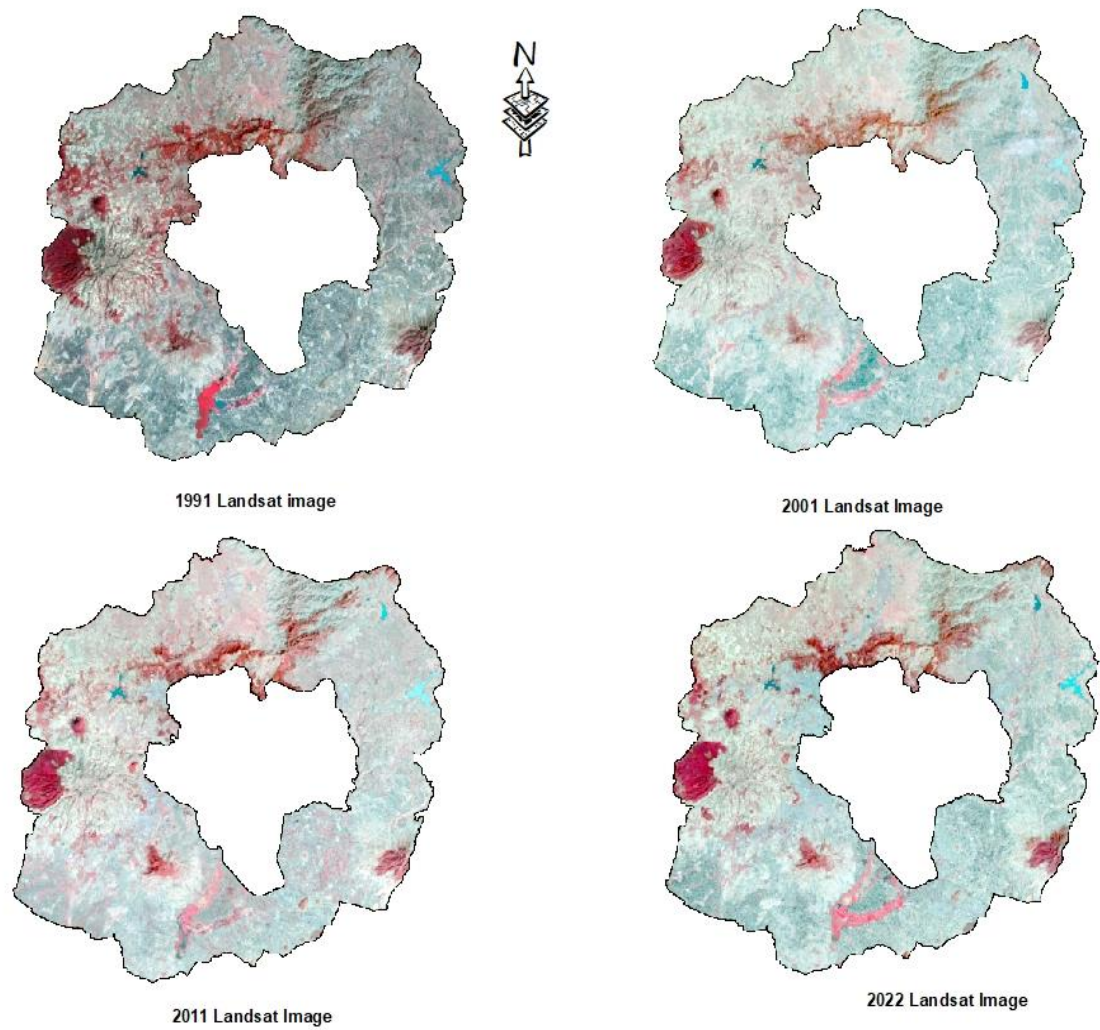


Figure 2: Landsat images of 1991, 2001, 2011, and 2022 used for classification

3.2 Method of Data Analysis

Geographical information systems (GIS) together with remote sensing data used to study the emerging urban sprawl of Segher City using digital satellite images. Basic satellite image processing procedures like layer stacking, image enhancement, and improvement processes are done for the raw satellite images to obtain clear pixels for performing classification analysis (Azadi, 2012). The data analysis will be performed using ERDAS Imagine 2015 and ArcGIS 10.7.1 software for preprocessing and image classification as well as accuracy assessment

3.2.1 Land Use Land Cover Analysis

Using the satellite images Layer stacking is done, also known as band stacking or image stacking, is a process in remote sensing where multiple images or spectral bands are combined into a single multi-band image Jensen, J. R. (2015). This process is crucial for land use classification, as it allows the integration of information from different spectral bands to enhance the accuracy of the classification. The images resembled each year using nearest neighbor method and convert all images to Adinda coordinate system. Using ERDAS imagine Contrast Enhancement is applied to Enhances the visibility of features by stretching the range of pixel values. This process is essential for land use classification as it enhances the separability of different land cover types, making classification more accurate.

Land use and land cover classifications are done by a supervised classification algorithm for the satellite images. From the classified images, the urban land features are extracted from the raster. A modified version of the Anderson LULC classification system Anderson (1976) used in this study. The classification scheme and detailed descriptions are given in Table 2.

The supervised classification system, particularly the Maximum Likelihood Algorithm, is widely used in image classification due to its effectiveness (Huang et al., 2002; Hamad et al., 2018). This algorithm was chosen for the study to perform supervised classification. It operates on the principle of assigning a pixel to a class based on the probability that the pixel's spectral signature matches the spectral signature of that class. Each class is represented by a Gaussian probability density function, which is characterized by its mean vector and variance-covariance matrix

across all spectral bands. By computing these parameters, the algorithm can determine the statistical probability of a pixel belonging to each class, facilitating accurate classification into different land use and land cover categories. For this study, a minimum of 50 samples for each land cover category is a good ‘rule of thumb’ as a starting point ensuring robust classification accuracy results.

Table 2: Land use land cover categories description

	Class name	Description
1	Urban or built-up Land	Residential, commercial services, industries, and transportation and telecommunication utilities.
2	Agriculture	Cropland, pasture, and other agricultural land
3	Bare land	Bare Rock/Sand Clay
4	Waterbody	rivers and lakes
5	Wetland	swampy and marshes
6	Rangeland	Grasslands; grazing land
7	Forest land	Land spanning at least 0.5 ha covered by trees and bamboo

3.2.2 Post-Classification comparison

The land use land cover change in the urban expansion identified by analyzing the classified multi-temporal satellite images (Shi, 2013) of 1991, 2001, 2011, and 2022. A multiple-date post-classification comparison change detection algorithm will be used to determine changes in land cover in the 30-year time. According to A study by Liu et al. (2010) post-classification comparison has been widely applied in various fields, including: Detecting changes in urban areas, including the growth of built-up areas and the reduction of green spaces.

3.2.3 Accuracy assessment

A map accuracy assessment should always follow a classification to evaluate the quality of the classification. This involves using sample points measured from Google Earth about the each land use class at the study sites. Ground truth points should be randomly distributed across the study area. A stratified random sampling design, where samples are selected from each class, is recommended. The major advantage of this approach is that it ensures all map categories are sampled. However, this design requires knowing each class in the study area therefore be conducted after the map has been produced.

Samples should be distributed between the classes, balancing between equal sample size per class and proportional allocation. In proportional allocation, the overall sample size is allocated to each class based on the area of the category, so smaller areas receive a smaller proportion of the samples. In equal allocation, the overall sample size is distributed equally among all classes. Stratification is particularly useful for rare classes, ensuring there are enough samples in these categories. The minimum sample size should be at least 20 to 100 samples per stratum (Congalton and Green, 2008). For the study, A minimum of 50 samples for each land cover category is a good ‘rule of thumb’ as a starting point.

User accuracy: is calculated from the number of correct sample points in a class divided by the number of samples of that class in the map. It illustrates the probability of an unknown point on the map being correctly mapped.

Producer accuracy: is estimated from the number of correct sample points in a class divided by the number of points of that class in the ground truth data. unknown point in the field as well as of being correctly mapped.

Overall Accuracy: number of correctly classified samples divided by total number of sample

Kappa coefficient (κ) : is a statistical measure used to evaluate the accuracy of a classification or the agreement between two raters/observers. In the context of remote sensing and land use classification, the Kappa coefficient provides a quantitative assessment of how well the classified image agrees with ground truth data, A Kappa coefficient equal to 1 means perfect agreement where as a value close to zero means that the agreement is no better than would be expected by chance. Whereas high Kappa Values (≥ 0.81) shown the classification method is very accurate and reliable.

Kappa coefficient calculated

$$K = \frac{\sum_{i=1}^r X_{ij} - \sum_{i=1}^r (x_{j+*} x_{i+})}{N^2 - \sum_{i=1}^r (x_{j+*} x_{i+})}$$

Where

- r Number or rows in the error matrix
- X_{ij} number of observations in row i and column j
- X_{i+} total of observation in row i
- X_{j+} total of observation in row j
- N Total number of observations including in matrix

Source: Lilesand et al (2004)

3.3 Computation of Urban sprawl

This study investigates urban sprawl through the application of five key indices: the Urban Expansion Intensity Index (UEII), Normalized Difference Built-up Index (NDBI), Urban Index (UI), New Built-up Index (NBI), and Band Ratio for Built-up Area (BRBA). The UEII measures the intensity and rate of urban expansion over time, providing insights into the spatial growth patterns of urban areas. The NDBI, utilizing reflectance values from satellite imagery, effectively distinguishes built-up areas from other land cover types. The UI and NBI further refine this analysis by enhancing the detection of urban features through specific spectral band combinations, while the BRBA emphasizes the contrast between built-up areas and their surroundings by leveraging band ratio techniques. Together, these indices offer a comprehensive approach to quantifying and characterizing urban sprawl, enabling a nuanced understanding of urban expansion dynamics and informing sustainable urban planning strategies.

Urban Expansion Intensity Index

Urban Expansion Intensity Index, (i.e., UEII) could be used to evaluate the urban spatial expansion difference quantitatively. Additionally, UEII could be employed to recognize the preferences of urban growth and to compare the speed or intensity of urban land use changes in a certain period. Equation (1) depicts the formula to calculate UEII.

$$UEII_{it} = \left[\frac{ULA_{i,b} - ULA_{i,a}}{t} \right] / TLA_i * 100 \dots \dots \dots \text{Eq. 1}$$

Where “UEII_{it} is the annual average urban expansion intensity index of the (ith) zone in the period (t) ULA_{i; a} and ULA_{i;b} is the quantity of built-up area at periods a and b in (ith) spatial zone, respectively. TLA_i is the total area of (ith) spatial zone” (Al-sharif et al., 2017).

Normalized difference built-up index (NDBI)

The NDBI can enhance information about built-up land from remote sensing images. Combined with appropriate threshold selection, NDBI can be used to extract impervious surfaces from urban areas. It utilizes the difference and the ratio of short wave infrared (SWIR2) band 12 and

near-infrared (NIR) or band 8 to highlight the built-up areas as depicted in Eq.2 (Zha, Y., Gao, J., & Ni, S. 2003).

$$NDBI = \frac{B_{SWIR2} - B_{NIR}}{B_{SWIR2} + B_{NIR}} \dots \dots \dots \text{Eq. 2}$$

Where B_{SWIR2} and B_{NIR} are the surface reflectance values of the second short-wave infrared and near-infrared band, respectively.

Urban index (UI)

Urban Index (UI) was first introduced by Kawamura et al. (1996), based on a computer system using Landsat 5 TM band 7 and band 4 to utilize the brightness relationship of urban areas with the near-infrared (0.76–0.90 μm) and mid-infrared (2.08–2.35 μm) spectrum. It makes use of short wave infrared (SWIR1) or (B11) and NIR channel or (B8) (Kawamura et al., 1996) and Xu, H. (2008).. UI can be calculated using Eq.3

$$UI = \frac{B_{SWIR1} - B_{NIR}}{B_{SWIR1} + B_{NIR}} \dots \dots \dots \text{Eq. 3}$$

where B_{SWIR1} and B_{NIR} are the surface reflectance values of the first shortwave infrared and near-infrared bands, respectively.

New Built-up Index (NBI)

The new built-up index (NBI) was proposed by observing the spectral response of different land covers in the RED , NIR and SWIR bands, based on the fact that the spectral response of barren land is greater than the other land covers in the previous bands (Jieli, 2008) defined the index as follows Eq.4

$$NBI = \frac{B_{RED} * B_{SWIR2}}{B_{NIR}} \dots \dots \dots \text{Eq. 4}$$

Where B_{RED} , B_{SWIR2} , and B_{NIR} are the surface reflectance values of the visible red band, the first shortwave infrared and near-infrared band, respectively.

Band Ratio for Built-up Area (BRBA)

Waqar (et al., 2012) introduced two new indices named, respectively, band ratio for the built-up area (BRBA) and normalized built-up area index (NBAI). Both metrics were employed to extract built-up areas of Islamabad City, Pakistan. To effectively discriminate impervious surface areas, the indices make use of Red or band 4 and SWIR₂ or band 12 as shown in Eq.5.

$$BRBA = B_{RED} / B_{SWIR2} \dots\dots\dots \text{Eq. 5}$$

Where B_{RED} and B_{SWIR2} are the surface reflectance values of the visible red band and the second shortwave-infrared, respectively.

Normalized built-up area index (NBAI)

The NBAI was designed by Waqar et al. (2012) to extract bare soil and built-up areas from Landsat imagery. To delineate the impervious surface from the previous using the bands, Green (band 2), SWIR1 (band 11), and SWIR2 (band 12) as shown in Eq.6

$$NBAI = \frac{B_{SWIR2} - B_{SWIR1}}{B_{GREEN} + B_{SWIR2} + B_{SWIR1}} \dots\dots\dots \text{Eq. 6}$$

Where B_{GREEN} , B_{SWIR1} , and B_{SWIR2} are the surface reflectance values of the visible green band, first shortwave infrared and second shortwave infrared, respectively.

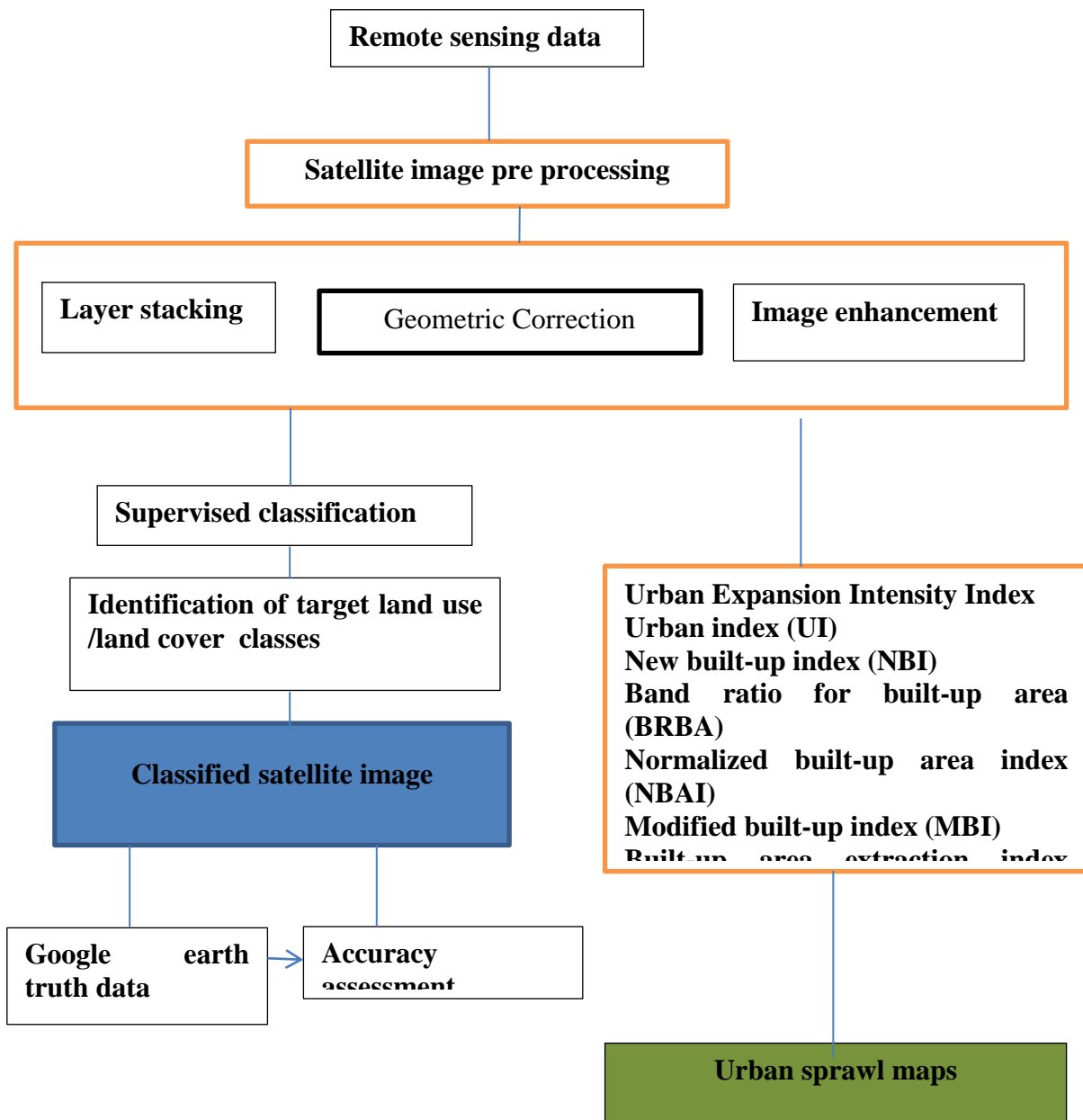


Figure 3: work flow of the study

4. RESULTS

4.1 Accuracy Assessment

The accuracy assessment table provides a detailed overview of the classification accuracy for each land cover class in the study area for the years 1991, 2001, 2011, and 2022 is present on Table 4. Based on the table presents a comparison of User's Accuracy (UA) and Producer's Accuracy (PA) for different land cover classes Agriculture, Rangeland, Bare land, Forest, Built-up Area, Wetland, Water body classes across different years (1991, 2001, 2011, 2022). Overall Accuracy and Kappa Coefficient are also included for each year. Agriculture and Rangeland both classes show consistently high accuracy for both users and producers across the years, with slight fluctuations but generally above 80%. Whereas; bare land User's Accuracy and Producer's Accuracy have improved from 1991 to 2011 but dropped slightly in 2022. Forest accuracy has shown improvement over the years but still remain relatively low compared to other classes. On the other hand Built-up Area has shown improvement over the years, with a significant increase from 1991 to 2001. But Wetland is a consistent high accuracy for both users and producers, although there is no data 2022 because change vanished. Water body: Similar to Wetland, there is a consistent high accuracy for both users and producers, with a slight increase over the years.

Overall Accuracy and Kappa Coefficient: The Overall Accuracy shows an increasing trend over the years, indicating an improvement in the classification performance of the model. The Kappa Coefficient, which considers the agreement between the model and random chance, also shows an increasing trend, indicating a higher level of agreement than would be expected by chance alone. The results indicate that the classification model has generally improved over the years, especially in distinguishing between different land cover classes. The high accuracy for Wetland and Water body suggests that these classes are easier to classify compared to others. The lower accuracy for Forest and Built-up Area indicates that these classes are more challenging to classify, possibly due to similarities in spectral characteristics. Overall, the trends in accuracy suggest that the classification model has been effective in accurately identifying land cover classes, with improvements seen over time.

Table 3: Accuracy Assessment of the Classification

Class	1991 Accuracy		2001 Accuracy		2011 Accuracy		2022 Accuracy	
	User's Accuracy (UA)	Producer's Accuracy (PA)	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Agriculture	88%	90%	82%	82%	84%	84%	86%	86%
Rangeland	90%	94%	84%	84%	86%	86%	86%	86%
Bare land	86%	75%	80%	80%	80%	80%	84%	82%
Forest	74%	59%	72%	72%	76%	76%	78%	74%
Built-up Area	56%	72%	72%	72%	72%	72%	76%	75%
Wetland	96%	94%	88%	88%	88%	88%	-	-
Water body	96%	96%	92%	92%	92%	92%	98%	98%
Overall Accuracy	83.14%		81.43%		99.71%		84.67%	
Kappa Coefficient	0.8036		0.7936		0.9968		0.8166	

4.2 Land use land cover change

The land use and land cover classification for each year from 1991 to 2022 in the study area are shown in Figure 3. Based on the classification result presented in Table 3 Built-up Area has shown a steady increase over the years, a built-up area in 1991 was 59.87 Km². This indicates the extent of urban development and infrastructure in the study area at that time. The relatively small size of the built-up area suggests that urbanization was still in its early stages in 1991. Whereas in 2001, the built-up area had increased to 91.87 Km² the significant increase reflects rapid urbanization and the expansion of infrastructure during this period. The growth of the built-up area between 1991 and 2001 suggests a period of rapid urban development and population

growth. The area under agriculture has shown fluctuating trends over the years. While there was a slight increase from 1991 to 2001. This could indicate changes in agricultural practices, such as intensification or abandonment of agricultural land. Rangeland has varied over the years, with a significant decrease from 1991 to 2001, followed by a slight increase by 2011, The area classified as bare land decreased sharply from 1991 to 2011.

Forest has remained relatively stable over the years, showing only minor fluctuations. This could indicate that forested areas have been relatively well-preserved in the study area. The area classified as wetland and water body has shown some fluctuations but overall remains relatively stable. However, the area classified as wetland has decreased significantly by 2022, which could indicate degradation or conversion of wetland areas.

The built-up area further expanded to 100.28 Km² by 2011. This continued growth indicates sustained urbanization and infrastructure development in the study area. The increase in the built-up area between 2001 and 2011 highlights the ongoing expansion of urban areas and the associated challenges of urban sprawl and land use change. The built-up area significantly increased to 200.07 Km² by 2022. This doubling of the built-up area since 2011 underscores the rapid pace of urbanization and infrastructure development in recent years. The considerable expansion of the built-up area by 2022 indicates the increasing pressure on land and resources due to urban growth and highlights the need for sustainable urban planning and management practices. Agriculture the area decreased slightly by 2011 and then more significantly by 2022. This could indicate changes in agricultural practices, such as intensification or abandonment of agricultural land. Rangeland further increase by 2022 these changes could be influenced by factors such as land degradation, land use changes, or conservation efforts. Bare land area classified increased in 2022 this could be due to factors such as urban expansion, land degradation, or natural regeneration processes.

Table 4: Land use land cover classification result

Class Name	Land use Land cover Classification of each year (Km²)			
	1991	2001	2011	2022
Agriculture	834.45	1095.90	1220.24	950.86
Rangeland	349.33	164.84	135.53	180.34
Bare land	184.24	118.56	8.57	139.53
Forest	170.13	133.79	137.98	135.56
Built up Area	59.87	91.87	100.28	200.07
Wetland	7.81	0.63	3.83	0.00
Waterbody	5.14	5.36	4.53	4.61
Total area classified	1610.97	1610.96	1610.97	1610.97

Overall, the trend of increasing built-up area in each year of classification reflects the ongoing urbanization and infrastructure development in the study area. This growth poses challenges such as land degradation, loss of natural habitats, and increased demand for services and infrastructure. Effective urban planning and management strategies are essential to address these challenges and ensure sustainable development in the region.

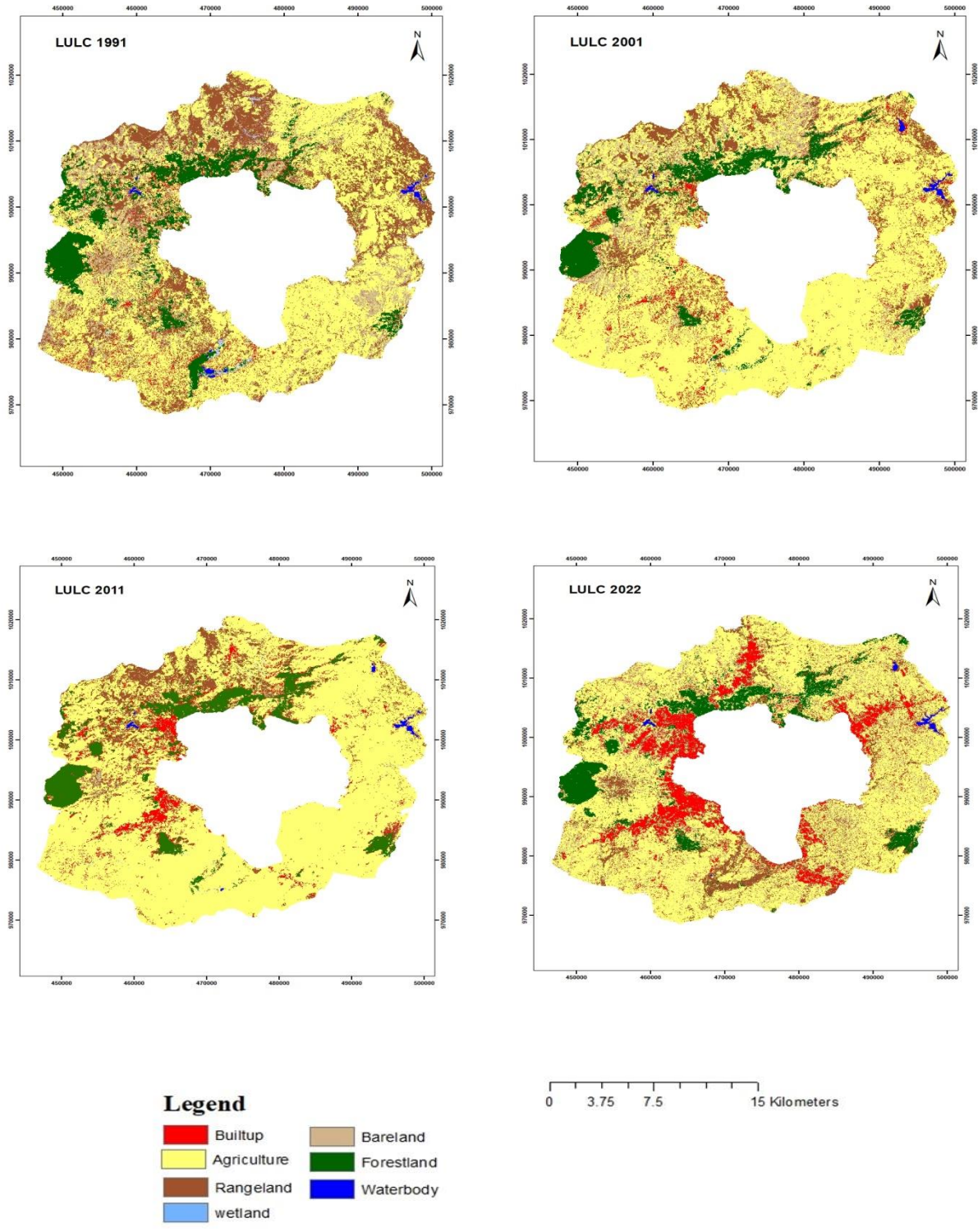


Figure 4: Supervised classification result of 1991. 2001, 2011, and 2022

4.3 Computation of Urban Sprawl Indices

4.3.1 Urban Expansion Intensity Index

The Urban Expansion Intensity Index provides a measure of the rate at which urban areas are expanding over time. A higher index value indicates a greater intensity of urban expansion during the specified period. The figure 4 shows the Urban Expansion Intensity Index for the years 1991-2001, 2001-2011, and 2011-2022: The Urban Expansion Intensity Index for the period 1991-2001 is 0.1987. This indicates a moderate intensity of urban expansion during this decade.

The relatively low index value suggests that urban areas were expanding at a steady pace during this time, possibly due to factors such as population growth, economic development, and infrastructure investment. The Urban Expansion Intensity Index for the period 2001-2011 is 0.0522. This indicates a low intensity of urban expansion compared to the previous decade. The decrease in the index value suggests that urban expansion slowed down during this period, possibly due to factors such as economic recession, changes in government policies, or saturation of urban areas.

The population growth in Urban residents often choose informal homeownership due to the absence of regulated rental housing and affordable rent levels (Watts and Blenkinsopp, 2021). However, this leads to squatter settlements arising from land scarcity and the unavailability of formal housing and land provision (Garrido, 2021). While informal housing may offer a sense of ownership, secure tenure, and hospitability (Watts and Blenkinsopp, 2021), it is crucial to understand the political economy behind it and its primary drivers.

Conferring to (Almayehu G., 2023) the lease system for urban landholding was first introduced in Ethiopia in 1993 through Proclamation No. 80/1993. This legislation aimed to address the increasing demand for urban land due to the country's rapid economic growth. However, because this law was enacted before the adoption of the constitution and the constitution does not specifically address urban land, it has been argued that the legal basis for this proclamation and subsequent lease laws is lacking.

In 2002, Proclamation No. 272/2002 repealed the initial lease system, only to be replaced again by the current legislation, Proclamation No. 721/2011. The objectives of this latest proclamation include satisfying urban land demand and ensuring good governance for the development of an efficient and transparent land market and administration system.

The law allows for two basic means of lease transfer: tender and allotment. Any person meeting the requirements is entitled to lease land, with all urban land being eligible for transfer under the lease system. City municipalities have the authority to allot land for specific purposes deemed of paramount importance to society, such as government offices, religious institutions, and public housing programs.

The Urban Expansion Intensity Index for the period 2011-2022 is 0.5631. This indicates a high intensity of urban expansion during this decade. The significant increase in the index value suggests a rapid pace of urban expansion, possibly due to factors such as rapid population growth, increased urbanization, and infrastructure development. The index values reflect the varying intensity of urban expansion during different periods, highlighting the importance of monitoring and managing urban growth to ensure sustainable development and mitigate the negative impacts of urban sprawl.

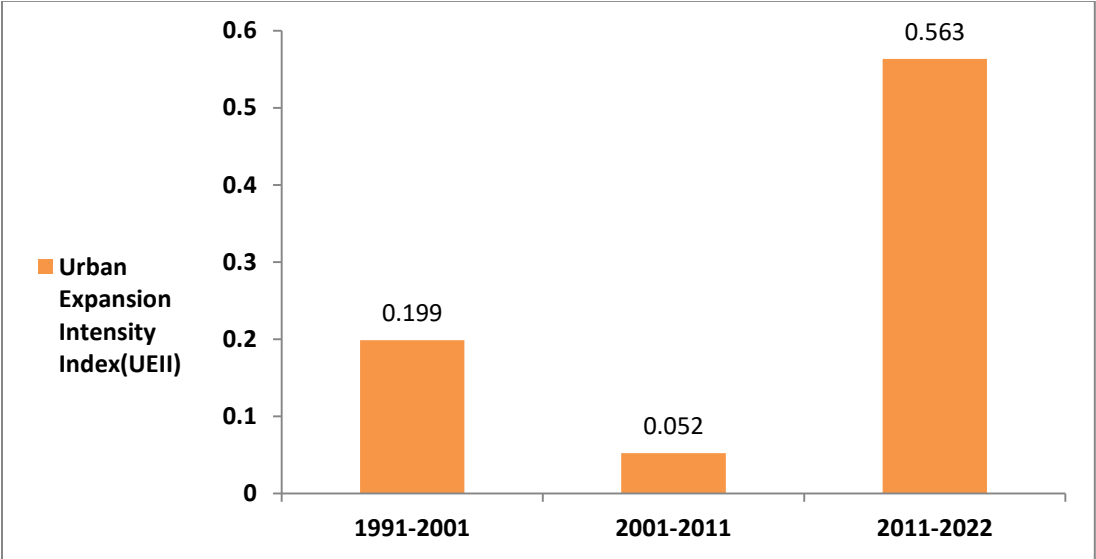


Figure 5: Graph urban Expansion intensity Index(UEII)

4.3.2 Normalized difference built-up index (NDBI)

The images provide the highest and lowest Normalized Difference Built-up Index (NDBI) values for Sheger City in the years 1991, 2001, 2011, and 2022 this shown on figure 5(a-d). The NDBI is a spectral index used to distinguish between built-up (urban) and non-built-up (non-urban) areas, with higher values indicating a higher proportion of built-up areas.

The highest value of NDBI in 1991 was 0.574257, indicating a large proportion of built-up areas, and the lowest value was -0.714286, indicating a small proportion of built-up areas. This shows that there are differences in the degree of urban development within cities, with some areas experiencing more intensive development than others.

By 2001, both the highest and lowest NDBI values increased, with the highest value reaching 0.59292 and the lowest value improving to -0.65625. This suggests a general trend of urban expansion and development across Sheger City during this period.

In 2011, the highest NDBI value decreased slightly to 0.522052, indicating a potential slowdown in urban expansion or a change in the pattern of development. However, the lowest NDBI value increased to -0.34439, suggesting that even areas with minimal urban development experienced some level of change.

By 2022, both the highest and lowest NDBI values decreased further, with the highest value being 0.297441 and the lowest value being -0.384549. This indicates a potential trend towards more balanced urban development across Sheger City, with less variation in the extent of built-up areas.

According to Shahfahad et al., 2022 used the NDBI to obtain the built-up area which was generated to a built-up density for each municipality. In the case of building density, studies directly used the values of the NDBI. Overall, the NDBI values suggest that Sheger City experienced significant urban expansion from 1991 to 2001, with a potential slowdown or change in the pattern of development from 2001 to 2011, and more balanced development by 2022. These findings can provide valuable insights for urban planning and development strategies to ensure sustainable growth and resource management in Sheger City.

4.3.3 Urban index (UI)

The Urban Index (UI) is a spectral index that provides a measure of urbanization or the extent of built-up areas within a city or region. It is derived from remote sensing data and is calculated based on the spectral characteristics of urban and non-urban areas. A higher UI value indicates a higher proportion of built-up areas, while a lower value indicates a lower proportion.

The table presents the highest and lowest UI values for Sheger City in the years 1991, 2001, 2011, and 2022. In 1991, the highest UI value was 0.485944, indicating a significant proportion of built-up areas, while the lowest value was -0.829787, suggesting a relatively low proportion of built-up areas. This indicates a variation in the extent of urbanization within the city, with some areas being more urbanized than others the extent shown in Figure 5 (e-g).

By 2001, both the highest and lowest UI values increased, with the highest value reaching 0.572368 and the lowest value improving to -0.830508. This suggests a general trend of urban expansion and development across Sheger City during this period.

In 2011, the highest UI value decreased slightly to 0.418752, indicating a potential slowdown in urban expansion or a change in the pattern of development. However, the lowest UI value increased to -0.480802, suggesting that even areas with minimal urban development experienced some level of change.

By 2022, both the highest and lowest UI values decreased further, with the highest value being 0.297441 and the lowest value being -0.384549. This indicates a potential trend towards more balanced urban development across Sheger City, with less variation in the extent of built-up areas.

Overall, the UI values suggest that Sheger City experienced significant urban expansion from 1991 to 2001, with a potential slowdown or change in the pattern of development from 2001 to 2011, and more balanced development by 2022. These findings can provide valuable insights for urban planning and development strategies to ensure sustainable growth and resource management in Sheger City.

4.3.4 New Built-up Index (NBI)

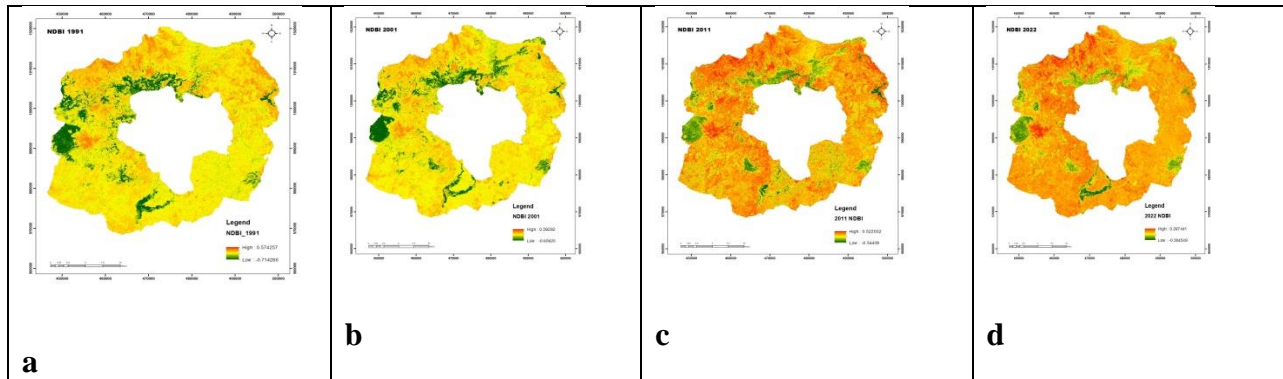
The NBI is a spectral index designed to quantify the extent of built-up areas within a city or region, with higher values indicating a higher proportion of built-up areas. In 1991, the highest NBI value was 2.30435, suggesting a significant proportion of built-up areas, while the lowest value was -2.26563, indicating a relatively low proportion of built-up areas. This indicates a variation in the extent of urban development within Sheger City, with some areas being more densely built-up than others.

By 2001, both the highest and lowest NBI values decreased, with the highest value reaching 2.17647 and the lowest value decreasing to -2.6. This suggests a general trend of urban expansion and development across Sheger City during this period.

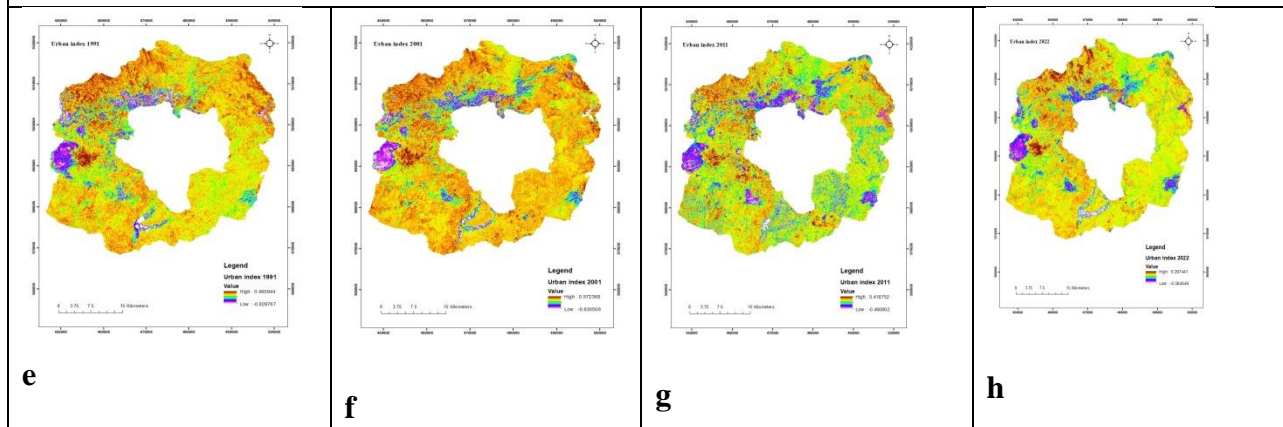
In 2011, the highest NBI value decreased significantly to 0.587335, indicating a potential slowdown in urban expansion or a change in the pattern of development. The lowest NBI value also decreased to -1.46329, suggesting that even areas with minimal urban development experienced some level of change.

By 2022, both the highest and lowest NBI values decreased further, with the highest value being -1.92791 and the lowest value being 0.69428. This indicates a potential trend towards more balanced urban development across Sheger City, with less variation in the extent of built-up areas extent shown in figure 5(i-1).

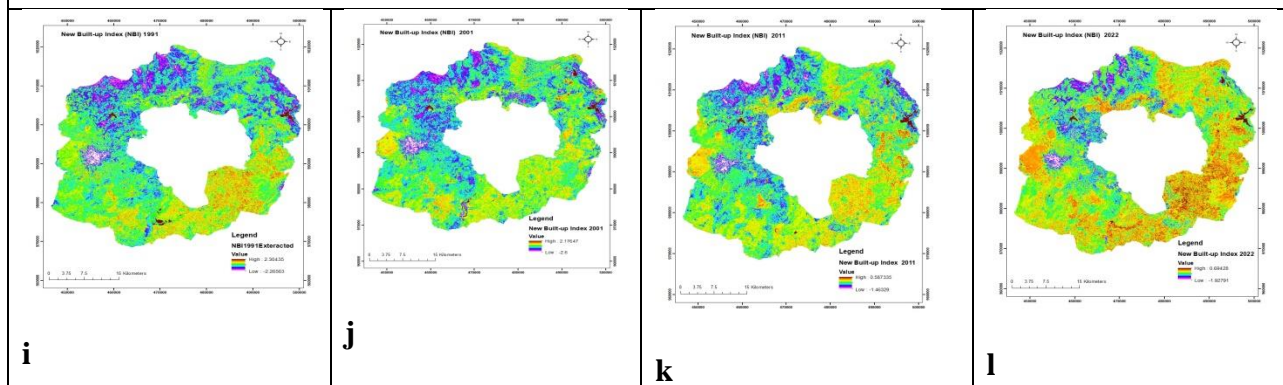
Overall, the NBI values suggest that Sheger City experienced significant urban expansion from 1991 to 2001, with a potential slowdown or change in the pattern of development from 2001 to 2011, and more balanced development by 2022.



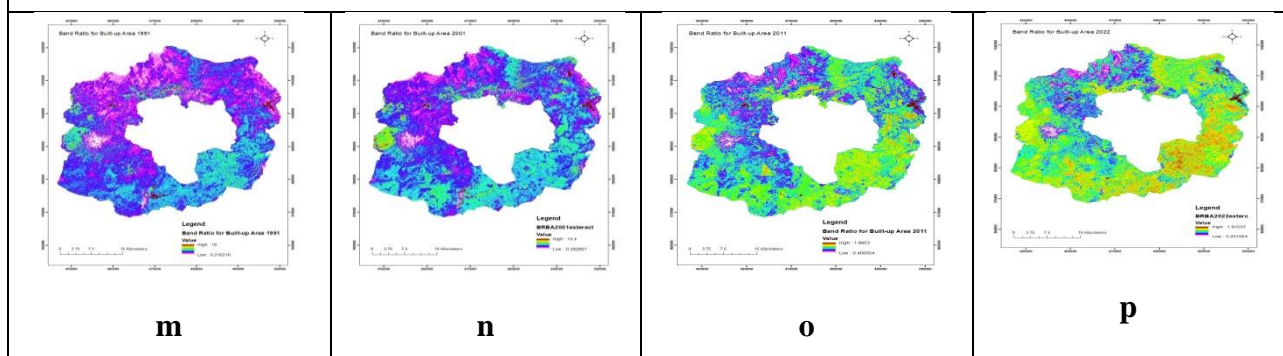
Normalized difference built-up index (NDBI) 1991, 2001, 2011, and 2022



Urban index (UI) 1991, 2001, 2011, and 2022



New Built-up Index (NBI) 1991, 2001, 2011, and 2022



Band Ratio for Built-up Area (BRBA) 1991, 2001, 2011, and 2022

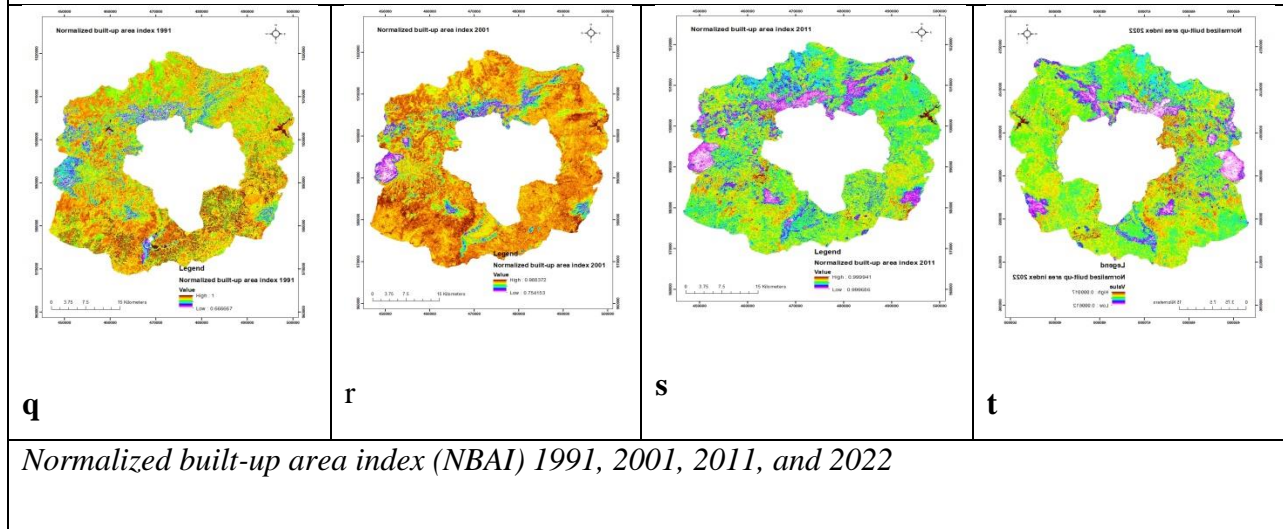


Figure 6: Spectral indices of Landsat image 1991, 2001, 2011, and 2022

4.3.5 Band Ratio for Built-up Area (BRBA)

The Band Ratio for Built-up Area (BRBA) is a spectral index that uses the ratio of reflectance values from different bands of remote sensing data to identify built-up areas within an urban environment. Higher BRBA values indicate a higher proportion of built-up areas, while lower values indicate a lower proportion in Figure 6(m-p) shows the BRBA of the study area.

In 1991, the highest BRBA value was 19, indicating a significant proportion of built-up areas, while the lowest value was 0.216216, suggesting a relatively low proportion of built-up areas. This indicates a variation in the extent of urban development within Sheger City, with some areas being more densely built-up than others.

By 2001, both the highest and lowest BRBA values decreased, with the highest value reaching 14.4 and the lowest value decreasing to 0.292887. This suggests a general trend of urban expansion and development across Sheger City during this period.

In 2011, the highest BRBA value decreased significantly to 1.9953, indicating a potential slowdown in urban expansion or a change in the pattern of development. The lowest BRBA

value also decreased to 0.400504, suggesting that even areas with minimal urban development experienced some level of change.

By 2022, both the highest and lowest BRBA values decreased further, with the highest value being 1.91557 and the lowest value being 0.251594. This indicates a potential trend towards more balanced urban development across Sheger City, with less variation in the extent of built-up areas. Overall, the BRBA values suggest that Sheger City experienced significant urban expansion from 1991 to 2001, with a potential slowdown or change in the pattern of development from 2001 to 2011, and more balanced development by 2022.

4.3.6 Normalized built-up area index (NBAI)

The Normalized Built-up Area Index (NBAI) is a spectral index used to quantify the extent of built-up areas within an urban environment. It is calculated based on the reflectance values from different spectral bands of remote sensing data, with higher NBAI values indicating a higher proportion of built-up areas.

In 1991, the highest NBAI value was 1, indicating a significant proportion of built-up areas, while the lowest value was 0.666667, suggesting a relatively low proportion of built-up areas. This indicates a variation in the extent of urban development within Sheger City, with some areas being more densely built-up than others these shows on the figure 6(q-t).

By 2001, both the highest and lowest NBAI values decreased, with the highest value reaching 0.988372 and the lowest value decreasing to 0.754153. This suggests a general trend of urban expansion and development across Sheger City during this period.

In 2011, the highest NBAI value decreased slightly to 0.999941, indicating a potential slowdown in urban expansion or a change in the pattern of development. The lowest NBAI value also decreased to 0.999686, suggesting that even areas with minimal urban development experienced some level of change.

By 2022, both the highest and lowest NBAI values decreased further, with the highest value being 0.999612 and the lowest value being 0.999917.

Table 5: Spectral indices of built-up and non-built-up Study area based on area

Built up and other classes derived from spectral indices (km²)								
	1991		2001		2011		2022	
	urban	non-urban	urban	non-urban	urban	non-urban	urban	non-urban
NDBI	15760.53	144881.7	16658.1	143984.2	30742.47	129899.8	21723.03	138919.2
UI	7794.36	152848	28702.1	131940	9787.86	150854	44565	116077
NBI	76556.5	84085.7	34455.1	126187	4564.62	156078	1025.73	159617
BRBI	21608.1	139034.2	40303.4	120339	70559.5	90082.7	53465.2	107177
NBAI	42103.3	118539	17473.8	143168	48814.7	111828	32840.1	127802

A comparison of urban and non-urban areas in Sheger City for the years 1991, 2001, 2011, and 2022 based on several spectral indices, including Normalized Difference Built-up Index (NDBI), Urban Index (UI), Normalized Built-up Area Index (NBAI), and others. These indices are used to differentiate between built-up (urban) and non-built-up (non-urban) areas, with higher values indicating a higher proportion of built-up areas.

The NDBI values show the extent of urbanization, with higher values indicating a higher proportion of built-up areas. The UI values also indicate urbanization, with higher values indicating a higher proportion of built-up areas. The NBI values provide a measure of the extent of built-up areas, with higher values indicating a higher proportion of built-up areas. The BRBI values indicate the ratio of built-up areas to total areas, with higher values indicating a higher proportion of built-up areas. Finally, the NBAI values provide a measure of the extent of built-up areas, with higher values indicating a higher proportion of built-up areas.

Overall, the trends in these indices suggest that Sheger City experienced significant urbanization and expansion of built-up areas from 1991 to 2022. This growth is evident in the increasing values of the indices for urban areas, indicating a higher proportion of built-up areas over time.

5. DISCUSSION AND CONCLUSION

5.1 Discussion

The existing global evidence, by S Chali E. et al., (2024) revealed that, with an average yearly growth rate of 13.36%, China's total urban area grew from 31,076 km² in 2001 to 80,887 km² in 2013. 33,080 km² of agricultural land were consumed during this time by this extensive urban growth. The land use and land cover classification, combined with the Urban Expansion Intensity Index (UEII), provides a comprehensive understanding of the dynamics of urbanization and land use changes in the study area from 1991 to 2022. The classification results with the urban expansion intensity to elucidate the patterns and implications of urban growth. According to (Akubia & Bruns, 2019), Urban Expansion Intensity Index(UEII reflects the future direction and potential of urban expansion and compares the speed or intensity of urban land-use change in different periods.

Urban expansion on agricultural land is driven by rapid population growth and is seen as a critical problem in Sub-Saharan African countries. The research performed by Moisa et al.,(2021) analyzed Addis Ababa City has spatiotemporal urban cover dynamics and predicted urban cover change by 2040 in the Sululta sub-city showed that urban expansion can reach quite high levels in the studied region. Also study showed by Edosa et al., (2024) Oromia region Sabata-Awas town has the built-up area of grown at a rate of 5.5 % each year, with notable gains from agricultural land accounting for 25 % of the growth and from forest land for 2.06 %. Studies revealed by Abebe et., al (2023) in Dukem town that land use and land cover change analysis results were shown the rapid increase in built-up areas expansions characterized by horizontal physical expansion led to dramatic changes against fertile agricultural land and sensitive environment

On this study Sheger city Built-up Area and Urban Expansion Intensity has shown a significant increase over the study period, reflecting the rapid urbanization and infrastructure development in the region. The UEII values for different periods corroborate these findings, indicating varying intensities of urban expansion. From 1991-2001 the built-up area increased from 59.87 km² to 91.87 km², with a UEII of 0.1987. This indicates a moderate intensity of urban expansion, suggesting a steady pace of development driven by factors such as population growth, economic

development, and infrastructure investment. Also from 2001-2011 the built-up area further expanded to 100.28 km², but the UEII dropped to 0.0522 on this lower intensity index suggests a slowdown in urban expansion, possibly due to economic recession, changes in government policies, or saturation of urban areas. Built-up area where doubled in 2011-2022 to reaching on 200.07 km², with a UEII of 0.5631, indicating a high intensity of urban expansion. This significant increase reflects rapid population growth, increased urbanization, and extensive infrastructure development during this period. The trend of increasing built-up areas, coupled with fluctuating UEII values, highlights the varying phases of urban growth and the importance of monitoring and managing urban expansion to ensure sustainable development.

From 1991 to 2022, agricultural land in the study area showed fluctuating trends, initially expanding from 834.45 km² to 1095.90 km² between 1991 and 2001. During this period, moderate urban expansion did not significantly affect agricultural land. From 2001 to 2011, agricultural land further increased to 1220.24 km², with urban expansion having less impact, as indicated by the lower Urban Expansion Intensity Index (UEII). However, from 2011 to 2022, agricultural land decreased to 950.86 km², coinciding with a high UEII, suggesting significant encroachment by rapid urbanization.

Grazing land, or rangeland, decreased sharply from 349.33 km² to 164.84 km² between 1991 and 2001 due to conversion to urban or agricultural land. Despite high UEII, this decline continued at a slower rate, possibly due to conservation efforts. Bare land initially decreased from 184.24 km² in 1991 to 8.57 km² in 2001 due to urban development and vegetation recovery, but increased to 139.53 km² by 2022, reflecting intense land cover changes. Forest cover remained relatively stable, with minor fluctuations from 170.13 km² in 1991 to 135.56 km² in 2022, indicating effective conservation measures. Wetlands decreased significantly from 7.81 km² in 1991 to 0 km² in 2022, highlighting the need for targeted conservation efforts, while water bodies remained stable with minor changes from 5.14 km² in 1991 to 4.61 km² in 2022. The combined analysis emphasizes the need for effective urban planning and sustainable land use practices to mitigate the negative impacts of rapid urbanization.

5.2 Conclusion

The land use land cover classification of Sheger City shows significant changes and trends from 1991 to 2022. The built-up area has steadily increased over the years, indicating rapid urbanization and infrastructure development. The built of area development was slightly slow from 1991 to 2001 while from 2011 to 2022 the expansion doubled.

The accuracy assessment shows valuable insights into the classification. Overall, the accuracy assessment table provides important information about the reliability of the land cover classification results, which can be used to improve future classification efforts and inform land management and planning decisions in the study area.

Various spectral indices were also used to evaluate the explanation of the built-up area in Sager City. From these indices UEII, NDBI, UI, UBI, BRBI, and NBAI indicate the expansion significantly higher since 2011. The evaluation showed a substantial agreement among the spectral discrimination index

In conclusion, compared to direct land use land cover classification, index-based methods, particularly using Satellite image bands, be efficient and effective for mapping built-up areas. These methods leverage the higher reflectance of built-up surfaces, making them easily distinguishable from other land types. This capability allows planners and decision-makers to quickly identify and estimate built-up areas in states and cities, enabling better decisions and more sustainable management practices.

Furthermore, this work highlights the potential for combining multiple spectral indices to enhance the mapping and analysis of impervious surface changes, urban expansion, and urban planning. By using these methods, researchers and practitioners can gain valuable insights for more effective decision-making and management of urban areas,

In comparison with supervised classification, built-up indices enable built-up areas to be mapped at a higher degree of accuracy and objectivity. The absence of training samples from the mapping makes subjective intervention from the human analyst redundant. A multi-scale and multi-temporal analysis is required to understand the urban development patterns. The traditional methods to collect information on urban parameters are outdated and cost a lot of resources. The

study provides a first milestone about the trends of the expansion within ten ten-year interval. In addition further study will be needed on the socioeconomic and environmental factors for the expansion of Sheger City.

RECOMMENDATION

Based on the research findings, the following recommendations are suggested for sustainable urban planning and development in Sheger City, Ethiopia: Continuously monitor urban growth using remote sensing and GIS techniques to understand the dynamics of urban sprawl and its impact on the environment.

- The study provides a methodological framework for mapping and quantifying urban sprawl, applicable to other cities. It confirms that the level of urban sprawl can vary depending on the methods used for quantification. Therefore, it is beneficial to use multiple methods to capture the multi-dimensional aspects of urban sprawl accurately.
- Research focused only on Sheger City and analyzed three time series for temporal analysis. Expanding the study area to include more domestic and international case studies is recommended to evaluate the applicability and accuracy of the findings.
- Develop and implement effective urban planning strategies to manage urban expansion, such as zoning regulations, land use planning, and infrastructure development plans.

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APPENDIXES

Point used for accuracy assessment

x	y	Classvalue	clascategori
481140	1006350	4	Agri
455310	1007040	7	Bare
456960	999060	4	Agri
474960	1007550	6	wet
458130	1000830	3	Range
479010	1014180	4	Agri
475590	975870	4	Agri
459390	977970	4	Agri
492990	980070	7	Bare
480450	987210	4	Agri
466020	990060	3	Range
455550	976620	4	Agri
483510	977010	4	Agri
475770	1015470	3	Range
480960	980820	4	Agri
454740	1008960	7	Bare
452310	1009170	7	Bare
481110	974490	4	Agri
481050	1011810	14	Forest
485010	979620	4	Agri
488550	979830	4	Agri
494310	1001610	3	Range
470640	1005180	4	Agri
492210	1010670	3	Range
464700	1002240	7	Bare
449160	989190	14	Forest
490620	991740	7	Bare
467910	1006500	4	Agri
485430	983490	4	Agri
462690	981570	4	Agri
483090	1007190	4	Agri
493410	988950	4	Agri
449670	984600	4	Agri
469230	1010580	4	Agri
459720	985740	4	Agri
475680	971100	3	Range
482580	984240	4	Agri
463320	1011720	3	Range
462330	1003140	14	Forest
467460	981240	3	Range

461250	1001730	4	Agri
490650	994050	4	Agri
449100	990630	14	Forest
476640	1011780	3	Range
449850	983970	4	Agri
464100	974880	4	Agri
491160	1016550	14	Forest
460650	989850	4	Agri
450990	1003830	4	Agri
463200	977310	4	Agri
469980	978240	8	water
493620	1006710	4	Agri
472440	1012800	3	Range
464100	1008360	7	Bare
493680	987660	7	Bare
474480	1011300	3	Range
496920	1008810	3	Range
494790	1011120	3	Range
490710	998160	3	Range
494430	992520	3	Range
450480	993630	14	Forest
464460	1010010	3	Range
463590	1011420	3	Range
466980	1007070	14	Forest
452880	999540	7	Bare
463470	1009140	3	Range
474180	1011600	3	Range
453540	992280	7	Bare
488850	1005600	3	Range
464400	1010700	3	Range
451080	1008720	7	Bare
466740	975720	6	wet
462840	970950	3	Range
462360	973920	3	Range
477240	1002390	14	Forest
469140	981690	3	Range
482130	1002990	14	Forest
459930	977490	6	wet
490680	985140	7	Bare
476700	1009650	3	Range
493230	1012860	3	Range
458280	999600	7	Bare
456180	1008930	7	Bare
452340	1003500	7	Bare

463860	983730	14	Forest
475470	1008570	3	Range
455280	997290	14	Forest
499470	1000710	3	Range
456870	998190	14	Forest
494070	999720	3	Range
467790	972780	14	Forest
454830	980430	3	Range
476850	1002720	14	Forest
494040	995100	7	Bare
462690	1005660	14	Forest
492120	986790	7	Bare
473100	1005300	14	Forest
457560	978810	7	Bare
457350	1007580	7	Bare
477210	1008120	7	Bare
453690	1000200	14	Forest
460950	996780	7	Bare
466620	972840	6	wet
449520	993510	14	Forest
492630	980070	7	Bare
449160	989610	14	Forest
453180	1002270	14	Forest
450360	993630	14	Forest
473430	975540	14	Forest
454260	991590	7	Bare
479490	1005930	7	Bare
465510	1000830	14	Forest
497460	997620	7	Bare
457710	994380	7	Bare
451890	1002420	14	Forest
480570	1004160	7	Bare
450330	976710	6	wet
481500	1015740	14	Forest
497820	1003110	7	Bare
471150	1009680	7	Bare
465450	1003830	14	Forest
461010	995100	14	Forest
454050	988380	7	Bare
468810	977460	14	Forest
466710	981030	14	Forest
450840	976350	6	Built
471720	1007730	14	Forest
475920	978090	6	Built

497790	1003500	8	water
497220	1002480	8	water
471960	1010100	6	Built
480900	1005270	6	Built
464130	973050	6	Built
497070	1002420	8	water
453420	994050	6	Built
475920	1005120	6	Built
496410	995700	5	wet
461580	976050	6	Built
497550	1002810	6	Built
473370	1006710	6	Built
462930	1003260	6	Built
464010	973080	6	Built
462630	994800	6	Built
499290	1004580	8	water
459060	985170	6	Built
457380	998400	6	Built
457860	999450	6	Built
497520	1002480	8	water
457050	977190	6	Built
457380	975120	6	Built
476040	1010730	5	wet
473100	979770	6	Built
457710	984690	6	Built
460440	1001850	8	water
471240	979260	5	wet
470070	974250	8	water
471690	974160	6	Built
459630	1002420	8	water
476580	1016310	5	wet
476790	1004580	6	Built
469320	975030	8	water
463680	971730	6	Built
469980	977040	5	wet
459360	978600	5	wet
456960	975420	6	Built
460770	998580	6	Built
471300	974760	5	wet
476280	1016370	5	wet
496260	1002450	8	water
497910	1001820	8	water
476250	1010790	5	wet
494580	994140	5	wet

460200	1002180	8	water
476190	1010640	5	wet
475800	1016430	5	wet
495990	1002300	8	water
470190	978330	8	water



Ground data collection for Accuracy assessment